

# Assimilating satellite radiance observations with a local ensemble Kalman filter

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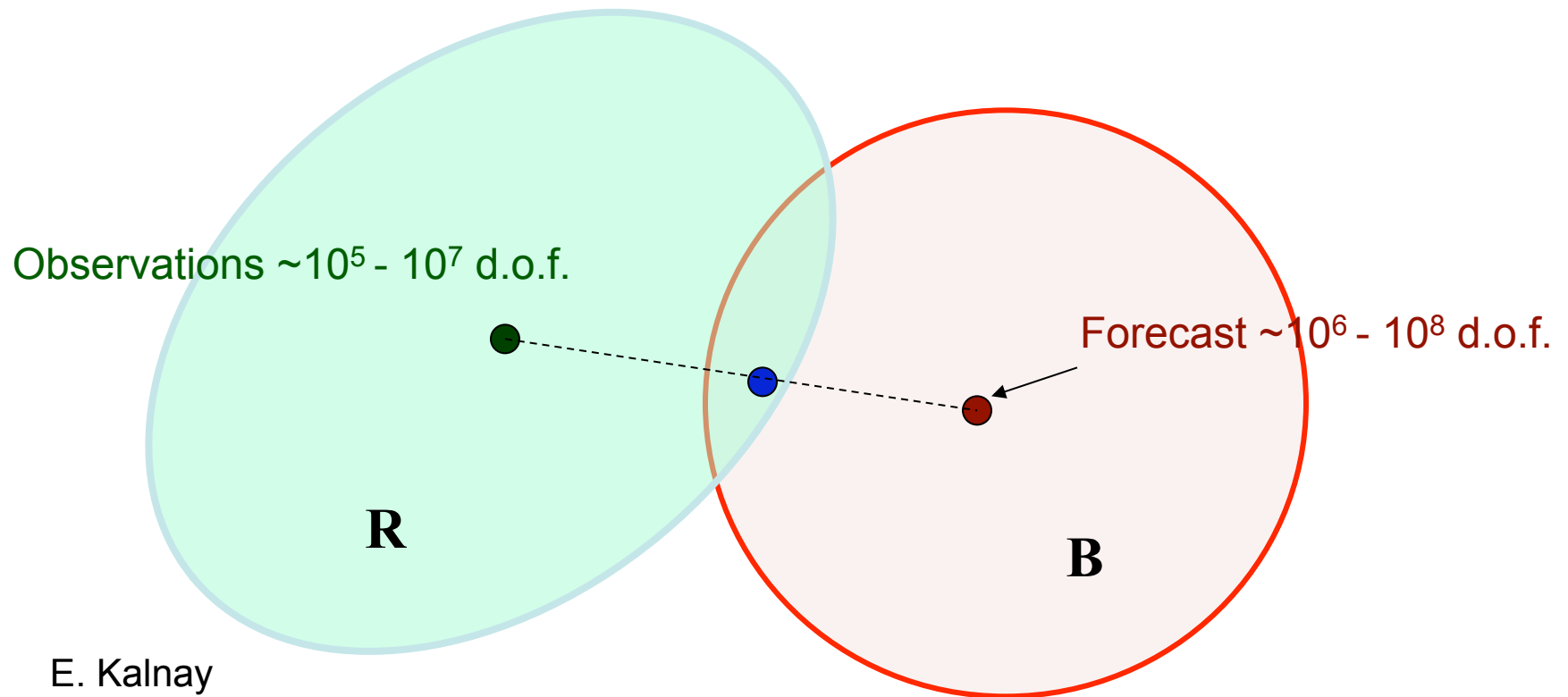
# Overview

- Ensemble-based assimilation schemes
  - Utilize flow-dependent forecast uncertainties.
  - Provide superior estimates than operational schemes because they account for “errors of the day.”
- Correcting forward model errors
  - Bias correction of radiances in assimilation schemes
  - Ensemble schemes can correct for these biases
- Assimilating satellite observations
  - Radiance observations improve forecasts in temperature and winds

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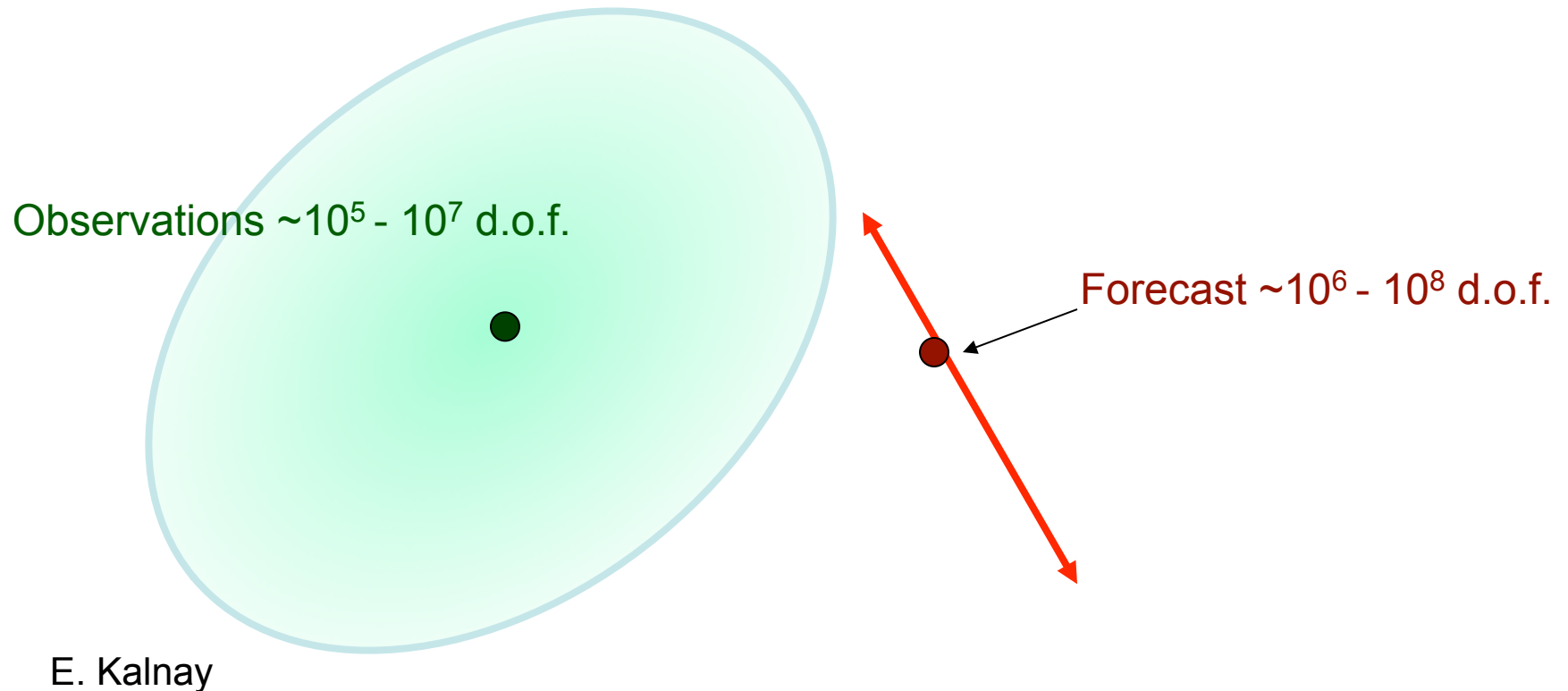
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# Covariances in 3D and 4D-VAR



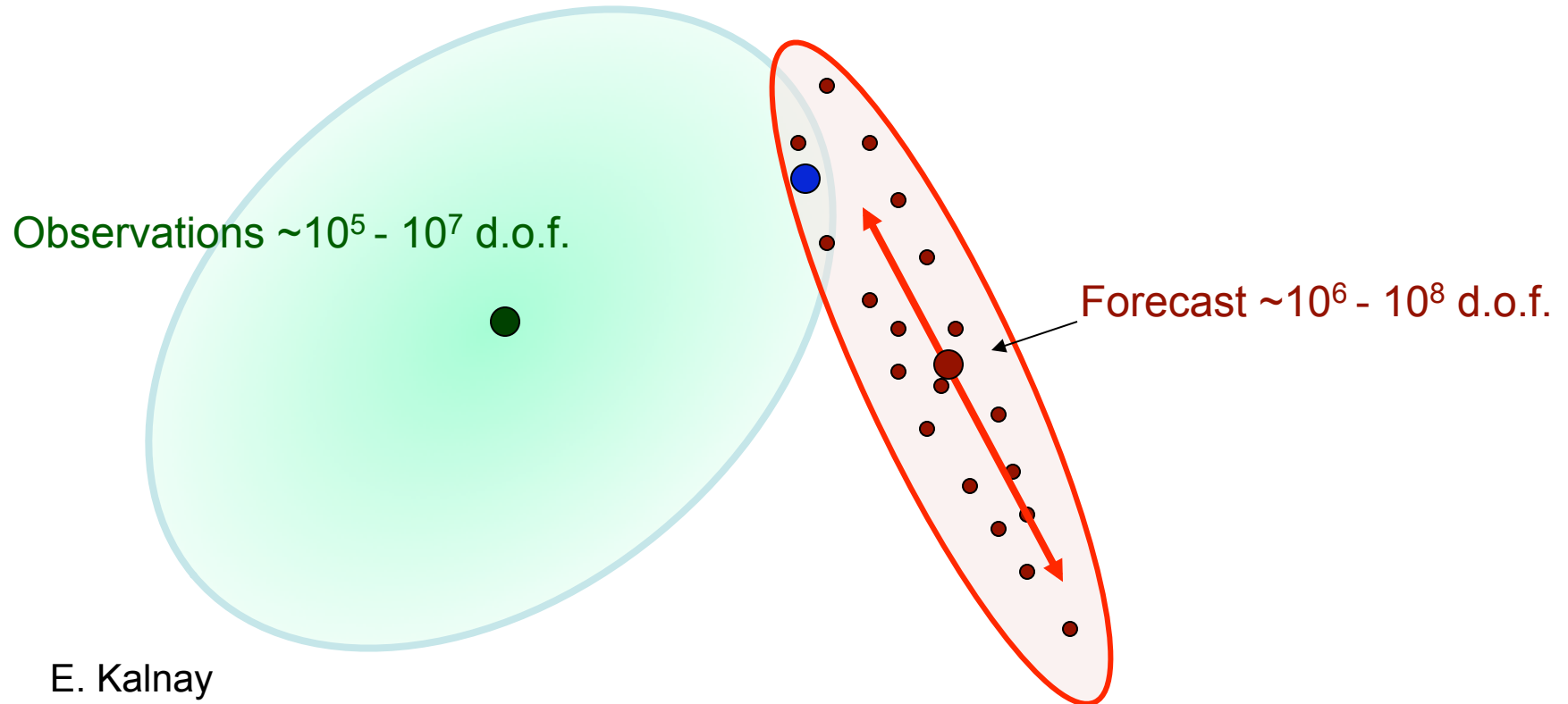
Operational systems assume that forecast errors are constant, homogeneous, and isotropic

# Structure of Forecast Errors



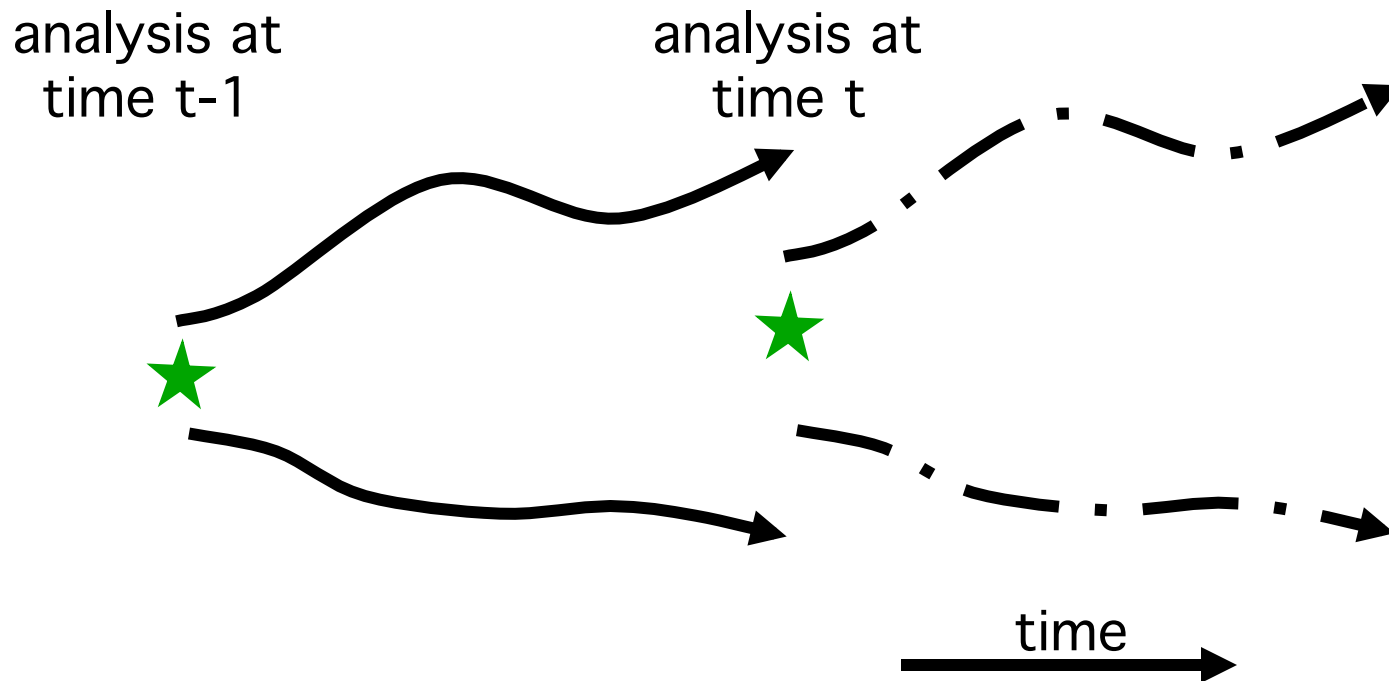
In reality, forecast errors lie on a low dimensional attractor and depend on the current atmospheric state.

# Ensemble Kalman Filter Schemes



Run an ensemble of forecasts from perturbed initial conditions to estimate the forecast error covariance

# Local Ensemble Transform Kalman Filter (LETKF)



LETKF finds the **best linear combination** of the ensemble members fitting **observations** at the analysis time.

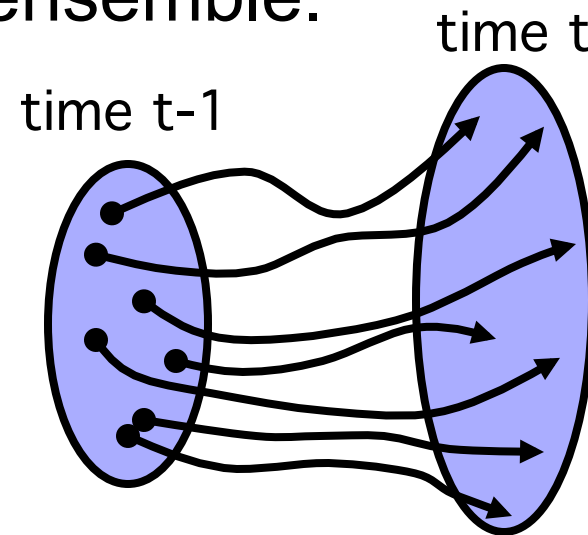
# Forecast Uncertainty

## Operational Schemes:

- Constant forecast error covariance matrix.
- Subject to “errors of the day”.

## Ensemble Schemes:

- Propagate the forecast error covariance with an ensemble.

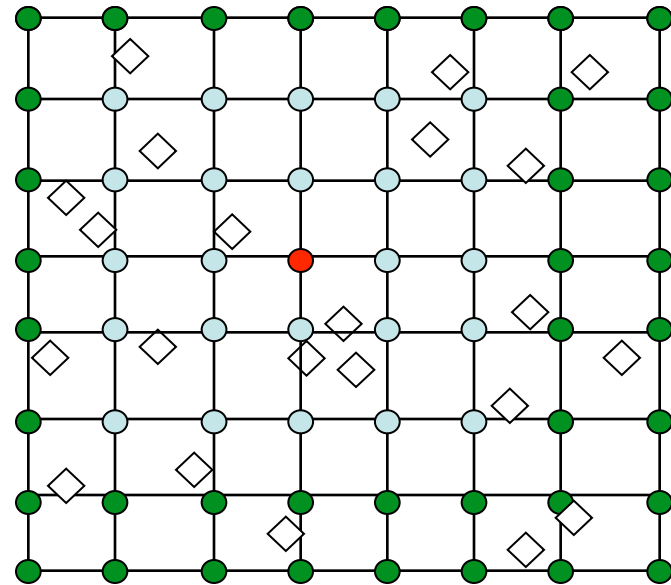


# Localization

Perform data assimilation in local patch (3D-window)

The state estimate is updated at the central grid **red** dot

All observations (**purple** diamonds) within the local region are assimilated

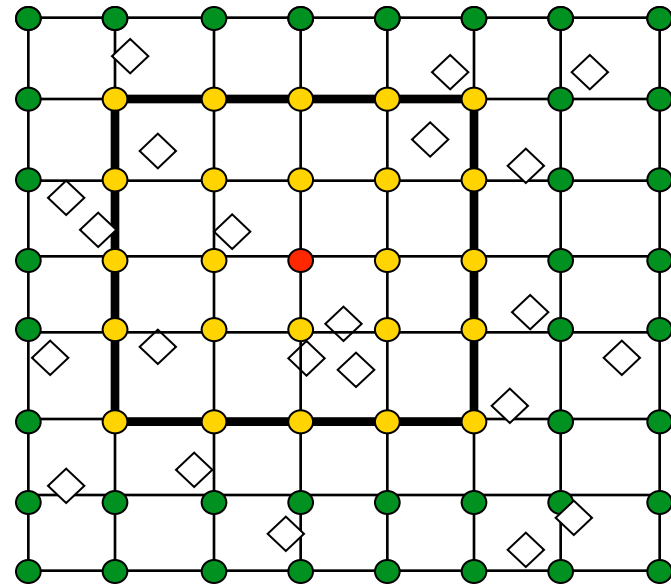


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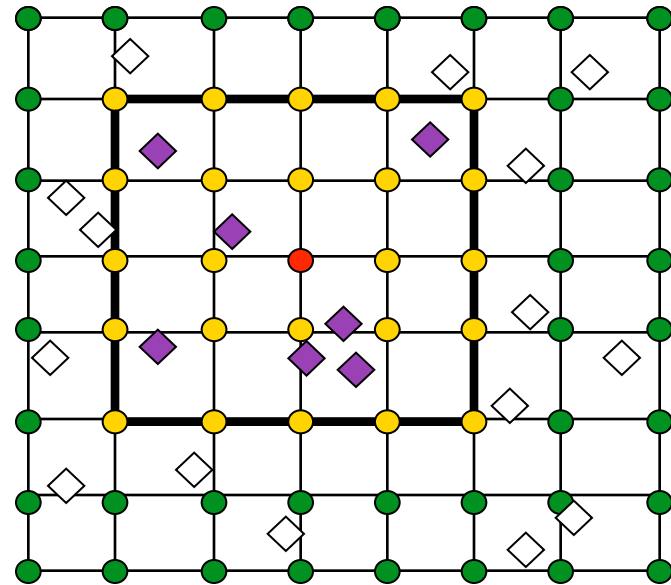


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# Features of LETKF

- LETKF is model independent and relatively simple to implement.
- Can parallelize the LETKF scheme.
- Gain further efficiency because matrix computations are performed in the space spanned by the ensemble.
- LETKF takes only 5 minutes on a 20 node PC cluster, which is comparable to the computational cost of operational schemes.
- LETKF should provide a more accurate analysis than operational schemes because it utilizes an evolving forecast error covariance.
- LETKF can adjust for “errors of the day.”

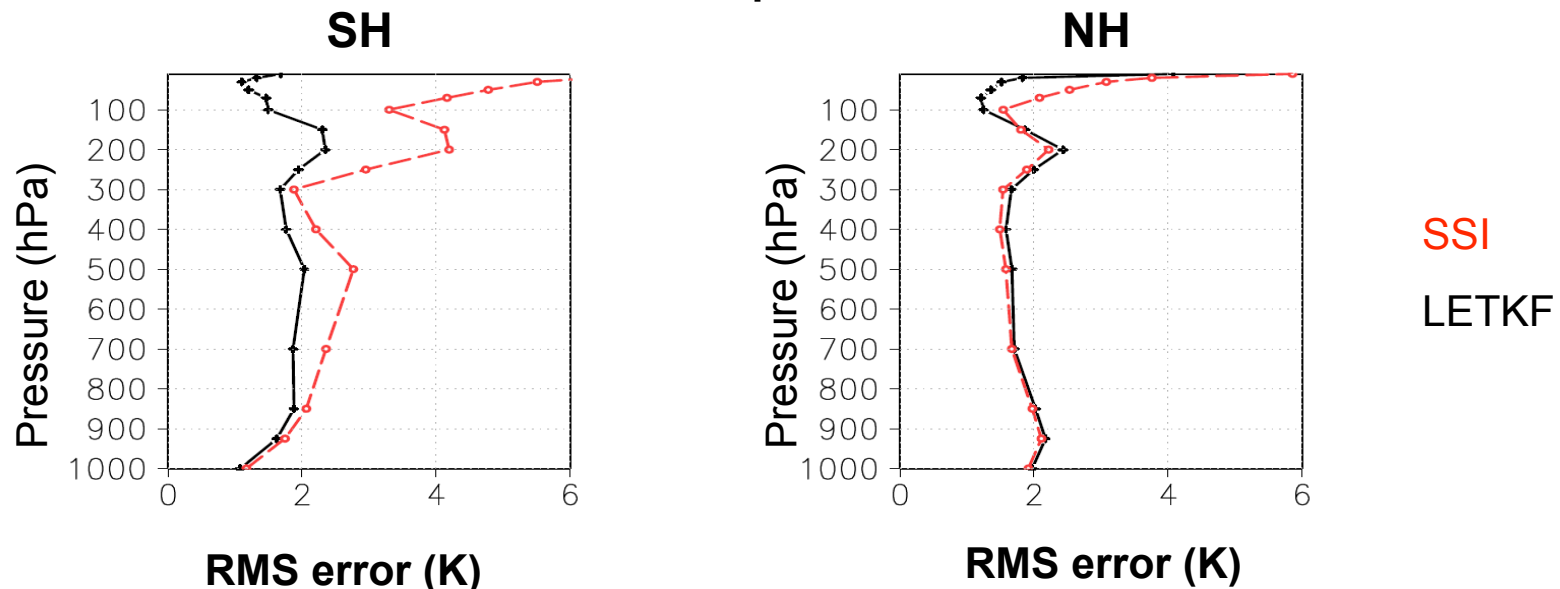
# Comparing LETKF to NCEP's 3D-VAR

- Use NCEP's 3D-VAR (SSI) and LETKF as the data assimilation scheme for T62 NCEP GFS.
- Assimilate all conventional observations for Jan-Feb, 2004.
- Analyses and forecasts are verified against operational T254 analysis.

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## 48 hour temperature



**In SH, the LETKF results  
are much better than SSI**

**In NH, the results  
are comparable**

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# Form of Satellite Observations

- Model for unbiased satellite observations is

$$y = \mathbf{h}(\mathbf{x}^{\text{true}}) + \boldsymbol{\eta},$$

- $\mathbf{h}$  takes model state variables into observation space
- $\mathbf{x}^{\text{true}}$  is the true model state
- $\boldsymbol{\eta}$  is unbiased random noise

- Biased satellite observation are assumed to be of the form

$$y = \tilde{h}(\mathbf{x}^{\text{true}}, \boldsymbol{\beta}) + \eta$$

- $\boldsymbol{\beta}$  is a vector of bias parameters to be determined.

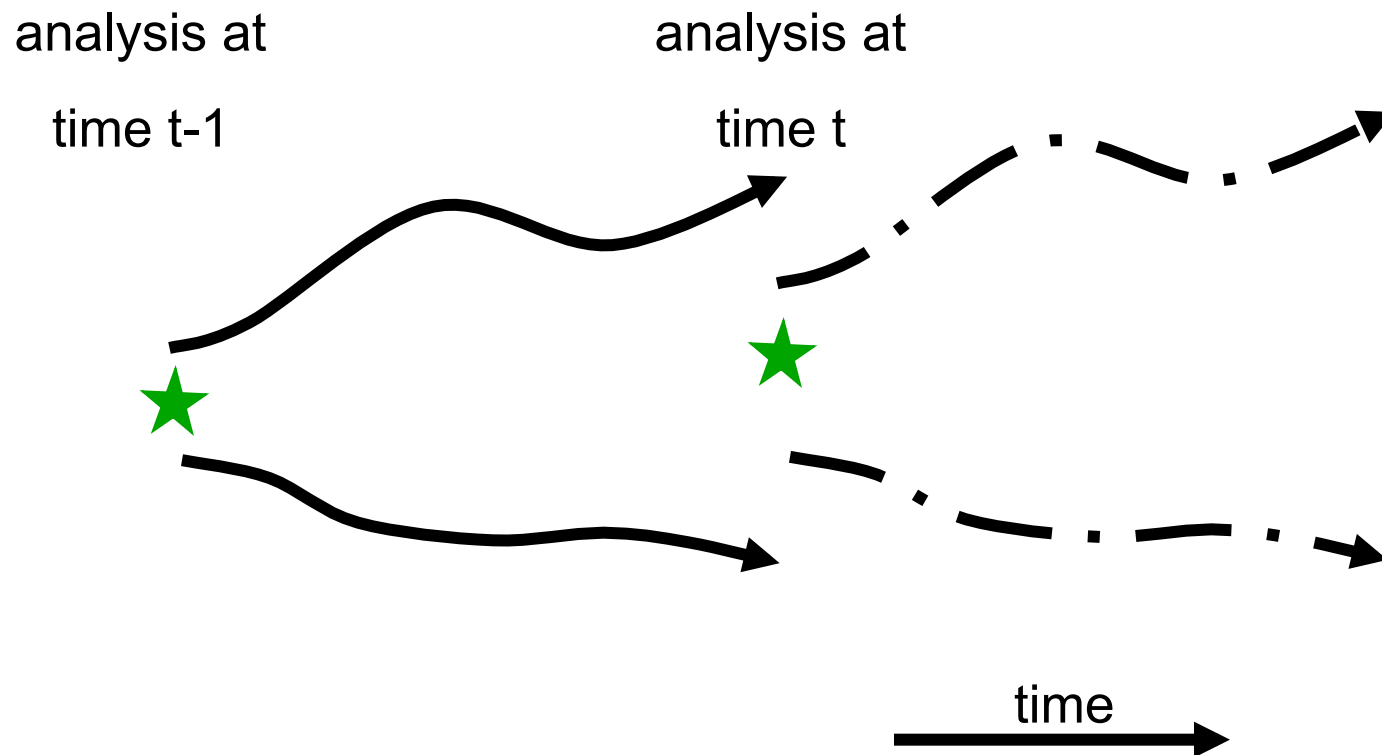
# Estimating Bias Parameters

- Biased satellite observation are assumed to be of the form

$$y = \tilde{h}(\mathbf{x}^{\text{true}}, \boldsymbol{\beta}) + \eta$$

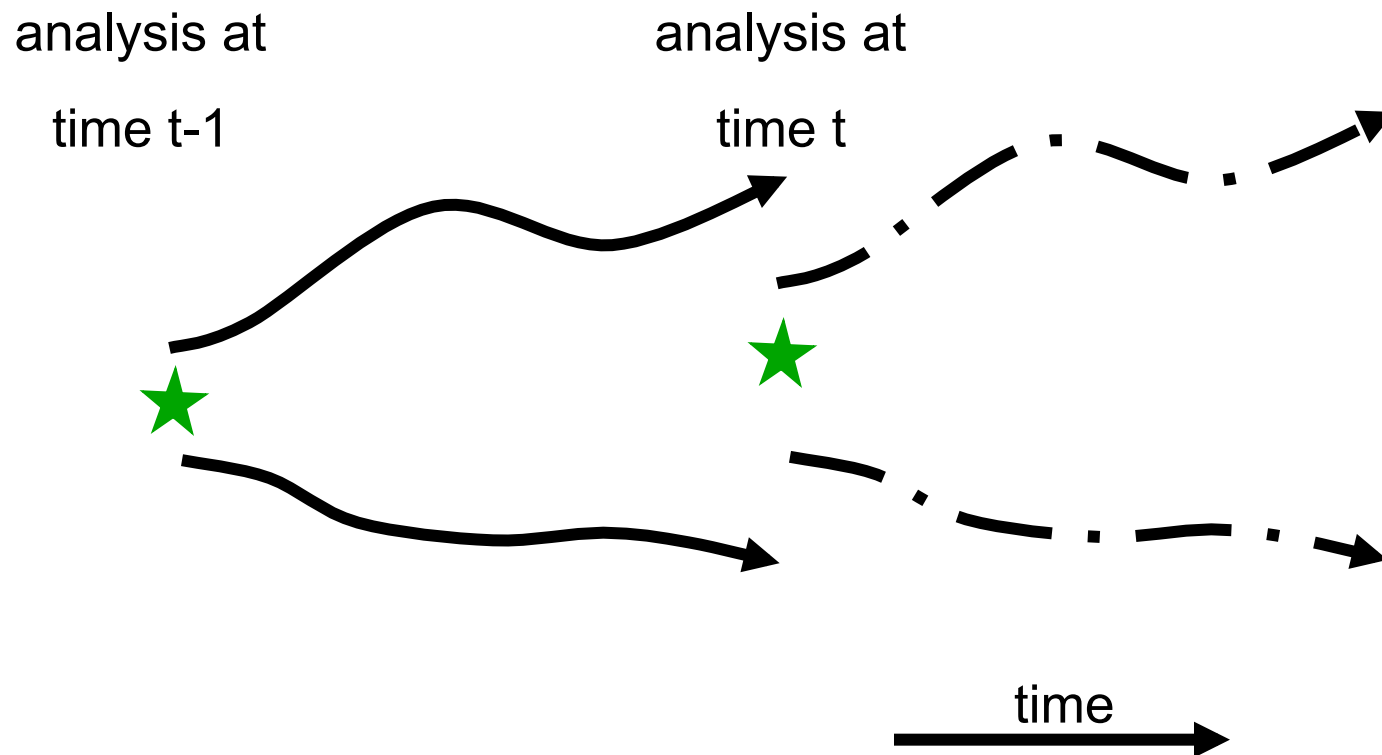
- $\boldsymbol{\beta}$  can be estimated online, during the data assimilation procedure (Derber and Wu, 1998; Dee and DaSilva, 1998; Baek et al., 2006)
- Ensemble-based schemes can incorporate a variety of bias correction techniques for radiances, including
  - Variational bias estimate and ensemble analysis (Miyoshi et al., 2010)
  - State space augmentation (Fertig et al., 2009)

# LETKF



LEKF finds the **best linear combination** of the model state ensemble members fitting the **observations** at the analysis time

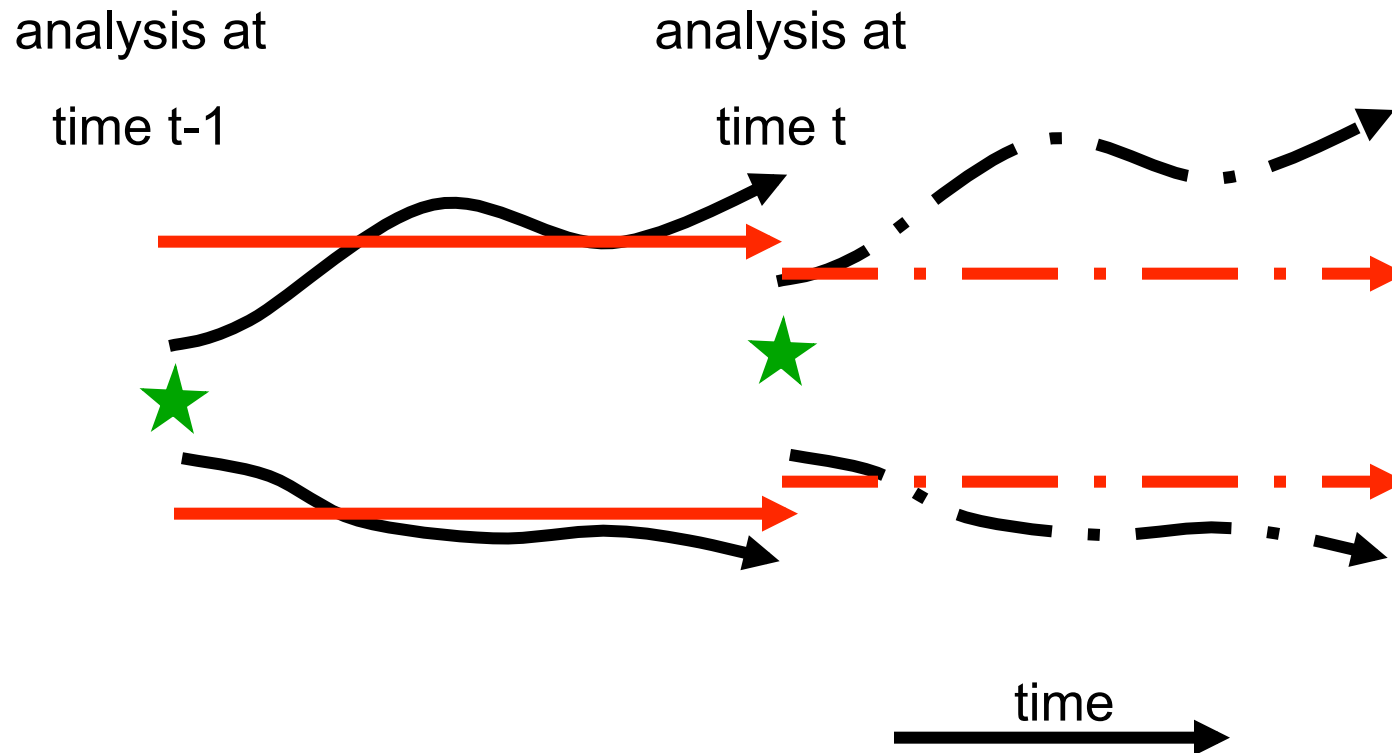
# LETKF with state space augmentation bias correction



Analysis  $\rightarrow$  [Analysis; Bias]

# LETKF with state space augmentation bias correction

Analysis → [Analysis; Bias]



Finds the **best linear combination** of the ensemble of model states **and bias parameters** fitting the **observations**.

# Perfect model experiments

## Perfect model scenario:

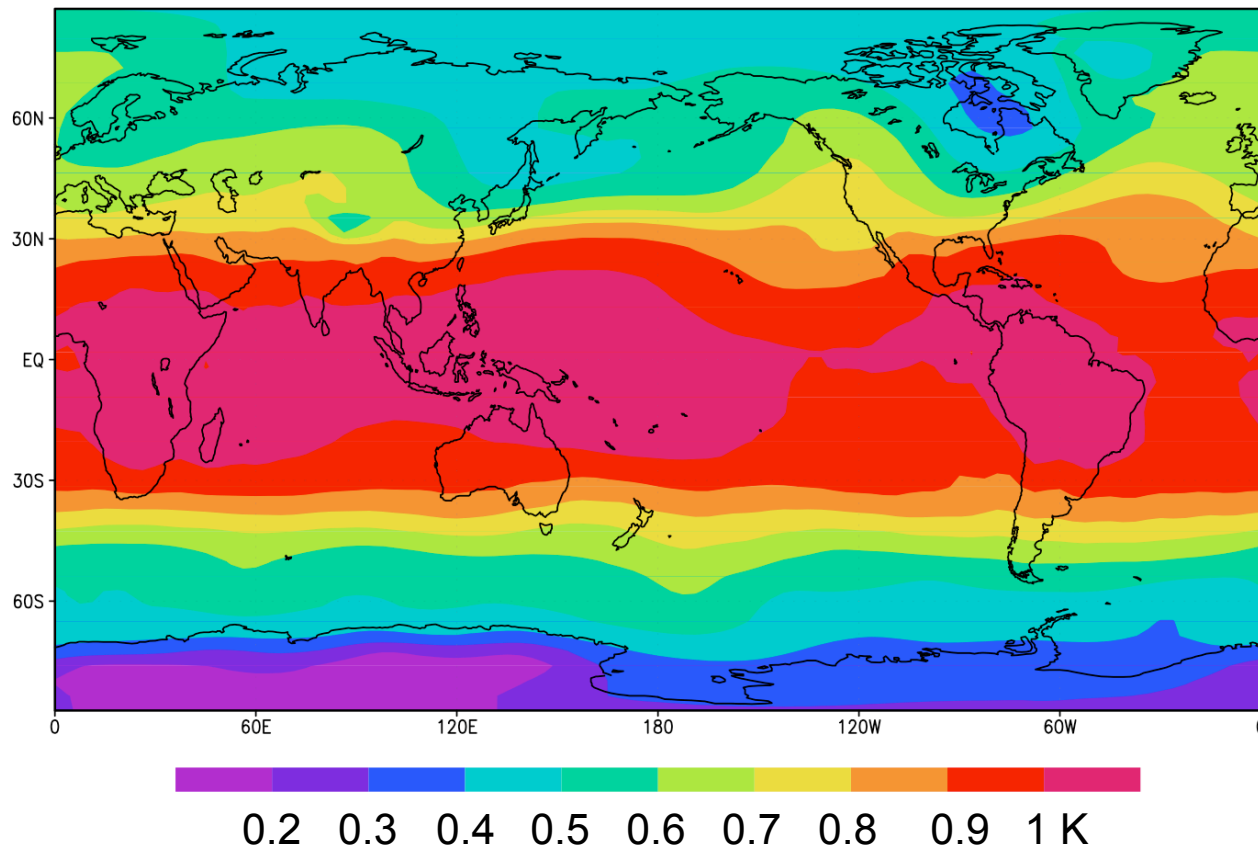
A “true” trajectory is generated by integrating the SPEEDY (low resolution, simplified GCM) model for two simulated months (Jan and Feb, 1982).

## Observations:

- Rawinsonde observations (U, V, T, Ps)
- Satellite observations
  - Use pCRTM to simulate 15 AIRS channels.
  - Created at every model grid point.
  - Bias simulated by assuming there is a fractional error in the satellite absorption coefficient (Watts and McNally, 2004).
- Satellite forward model uses raw pCRTM **without** the Watts and McNally term.

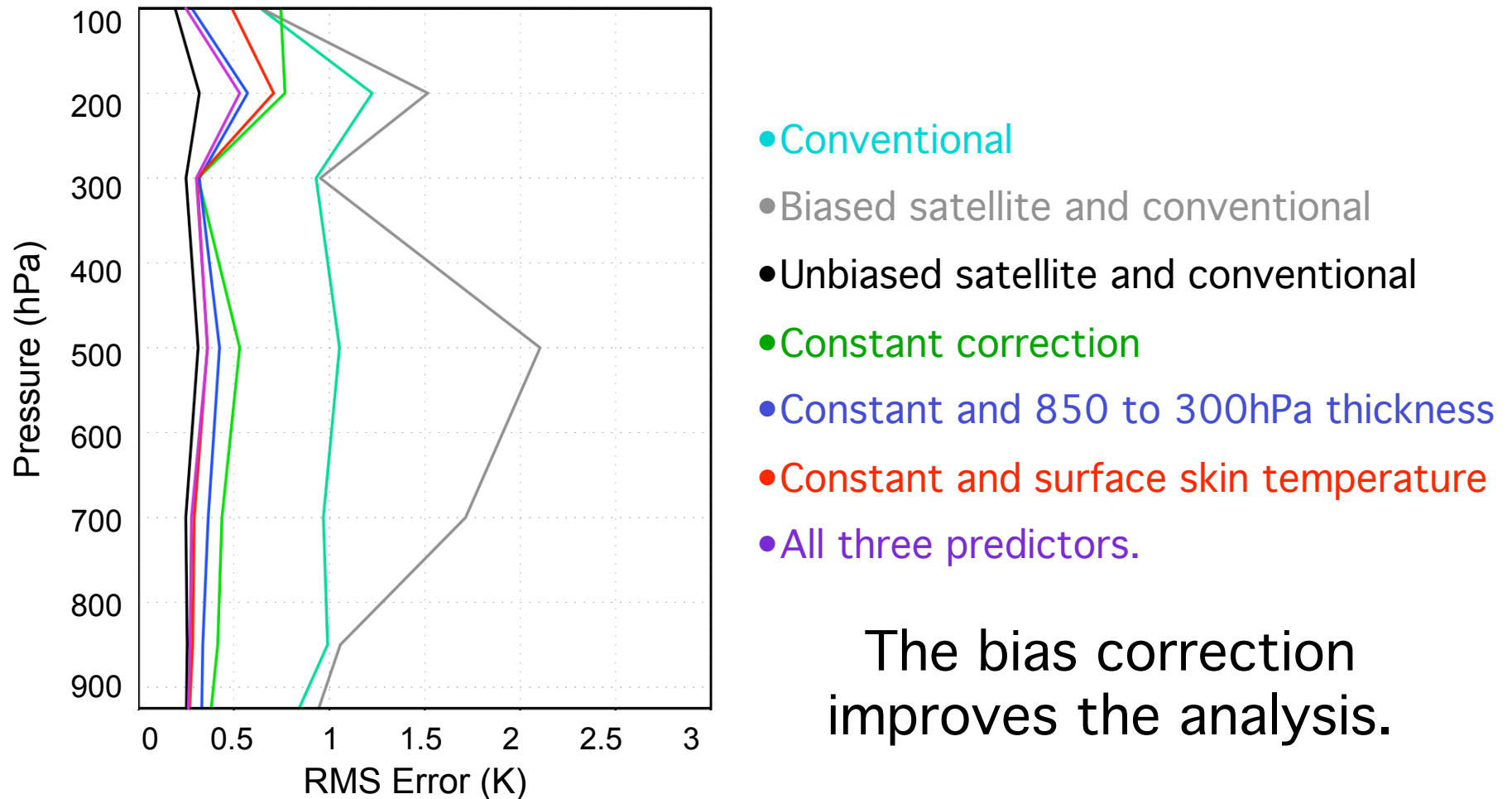
# Typical Simulated Satellite Bias

Time averaged satellite observation bias



The simulated bias has a similar structure to the true bias.

# Temperature Analysis RMS Error (global and Feb. average)



# Overview

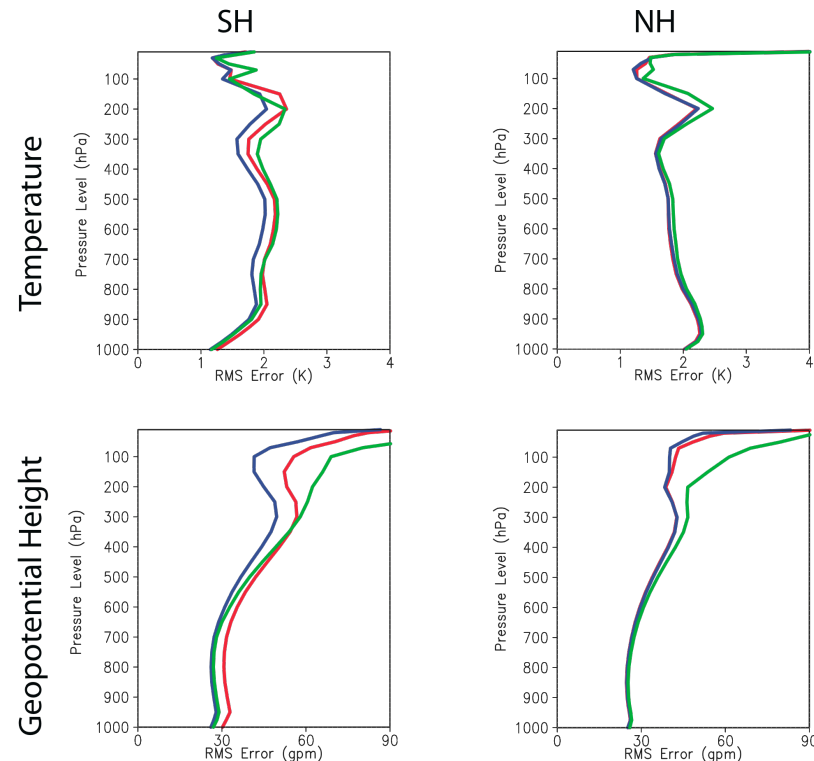
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# Assimilating radiances in NCEP GFS

- Use LETKF as the data assimilation scheme for T62 NCEP GFS.
- Assimilate all conventional observations and **AMSU radiances** for Jan-Feb, 2004.
- Bias correction terms are (1) constant, (2) scan angle, (3) skin temperature
- **Analyses and forecasts are verified against operational T254 analysis.**

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Conventional Observations

Radiances without bias correction

Radiances with bias correction

**Bias correction enables positive impacts from AMSU observations.**

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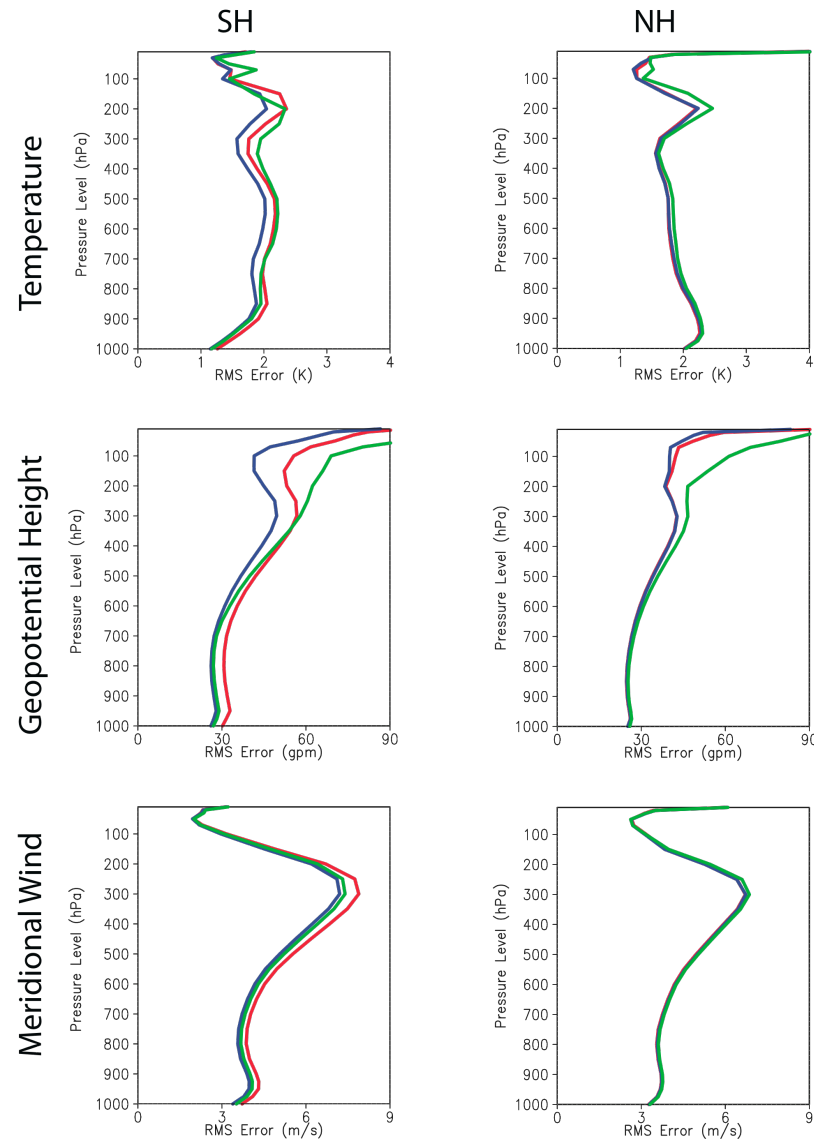
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Conventional Observations

Radiances without bias correction

Radiances with bias correction

**Cross-correlations enable positive impacts in wind field from AMSU.**



# Conclusions

- Ensemble schemes efficiently incorporate **flow-dependent forecast uncertainties** in a **model independent** way.
- LETKF improves the analysis obtained from 3D-VAR.
- LETKF can estimate radiance biases through forward model errors online efficiently.
- Bias correction improves analyses and forecasts in simulations with “perfect model” and real radiances.
- LETKF successfully uses cross-correlations between dynamic variables to **improve forecasts of unmeasured variables**.

# Biased AIRS observations

- Typical radiative transfer model:

$$h(\mathbf{x}) = \int B(T(p)) d\tau$$
$$\tau = \exp\left(-\int \kappa(p) \rho(p) dp\right)$$

- Assume the error in the satellite observations is in the absorption coefficient:

$$\kappa \rightarrow \gamma \kappa$$

$$\tau \rightarrow \tau^\gamma$$

- Watts and McNally (2004) find  $\gamma = 1.05$  for AIRS.